Penerbit Akademia Baru

Journal of Advanced Research Design

Journal homepage:
https://akademiabaru.com/submit/index.php/ard
ISSN: 2289-7984

Analytical Study on Emerging Trends in Cardiomyopathy Detection through Diverse Database Classification

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ARTICLE INFO

Article history:
Received 7 February 2025
Received in revised form 3 March 2025
Accepted 31 July 2025
Available online 11 August 2025

Keywords:
Cardiomyopathy; CMR; electrocardiograph (ECG); regression trees

ABSTRACT

Heart failure is a condition caused mainly by cardiomyopathy (CM) that is a major cause of mortality in the world. New developments in artificial intelligence (AI) here indicate that it can be of big aid when it comes to enhancing the accuracy of CM categorization. This paper provides an extensive analysis of the existing AI approaches towards the classification of CM and categorizes as well as contrasts different classifiers. This means that decision making based on these algorithms can be regarded as accurate or imprecise depending with the chosen datasets used in feeding the algorithm. This research assists the scientists in selecting the most suitable classification models for immediate use in the clinical setting. The results shown here clearly prove that machine-learning algorithms coupled with adequate databases can improve diagnostic precision and are feasible for real-time application in the identification of CM subtypes.

1. Introduction

Cardiomyopathies (CM) are categorized and a universally approved evidence-based classification system is still in progress [1,2]. CM (A disease of the heart muscle where the pumping function is impaired) In the case of a diagnosis, it is important to know which specific type of disease the person has [3,4]. Classification, however, is not so straightforward as CM are typically divided into three major types - dilated (DCM), hypertrophic (HCM) and restrictive/constrictive CM - with each type containing numerous subtypes. Objective classification of CM is important for guiding treatment and predicting the effectiveness of interventions (and therefore prognosis) [5,6]. Furthermore, researchers rely on understanding the different types of the disease to select subjects for research protocols or clinical trials and develop new treatment methods [7,8].

This article discussed recent developments in the categorization of CM. The goal is to find out the latest and most effective techniques that can give super-fast results with high accuracy. Understanding also how the different datasets can affect how well the proposed classifiers work. The paper will come up with some solutions for the challenges in CM classification that need some fixing

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https://doi.org/10.37934/ard.143.1.6583

and provide guidance for young researchers, emphasizing keep it simple when developing theories or methods where the complexity isn't always the answer.

This paper down research types in CM classification based on the data they use. There are three main groups: images, Electrocardiograph (ECG) signals and genetic data. The literature will be thoroughly examined to determine which methods provide the best accuracy and training time.

2. Cardiomyopathy Types

Genetic considerations have taken centre stage in the increasingly complex process of CM categorization. In order to assess therapy efficacy and prognosis, studies now precisely categorize subtypes utilizing a variety of methodologies. Better patient diagnosis and treatment outcomes are the result of this fitting with modern precision medicine.

CM classification has gotten a lot more detailed and genetic focused. Studies are now super good at sorting subtypes using all kinds of methods to see how well treatments work and predict outcomes. It is like modern medicine is getting all high-tech to help patients better [9,10].

There are different methods to classify cardiomyopathies accurately. Some ways look at how patients feel and what might happen to them, while others check out the heart's shape and function [11]. Furthermore, medical diagnostic instruments such as cardiac MRIs and ultrasounds are pretty trustworthy [12,13]. In HCM, hypertrophy location can impact prognosis [14,15].

CMR can be quite helpful in reducing the need for a biopsy to check myocardial fibrosis. However, when it comes to conditions like DCM [16], Arrhythmogenic right ventricular CM (ARVC) [17] and ventricular non-compaction CM (LVNC) [18], a biopsy is still crucial. It is super accurate in making tough diagnoses or classifications & spotting prognostic factors hard to see with other tests [18,19].

The substantial phenotypic variability of CM allows for precise genetic categorization. It offers a fresh viewpoint on CM categorization by linking genes with manifestations. There is distinct phenotypic variability and prognostic importance for some gene variants. The etiology may be better understood with the use of genetic categorization, which in turn aids medical research [20].

Pay close attention to the following details: Figure 1 shows a synopsis of the features and current, reliable criteria for classifying each subtype of CM. A number of correct CM classifications, however, still rely on the examination of a single component, in the absence of thorough study. A more accurate categorization may only be achieved by integrating pathological, imaging, cardiac electrophysiological and other clinical characteristics into a multimodal classification, as well as by combining several CM cohorts with gene alterations. For future studies on precise categorization, it is suggested to include other dimensions including immunological and metabolomics.

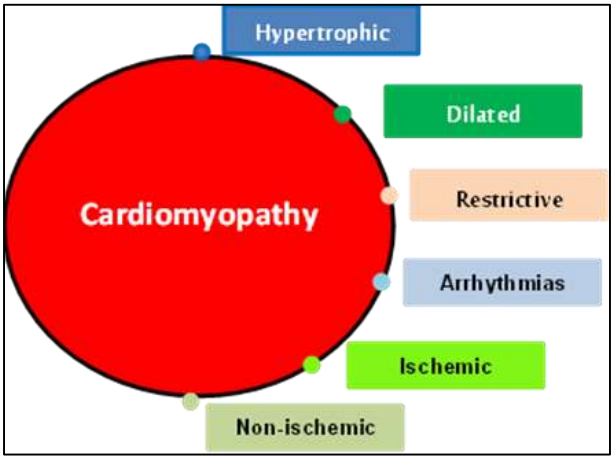

Fig. 1. CM types

3. Literature Review

3.1 Classification Technique According to Datasets

Adding another dataset could really help since different datasets have their own special features and patterns. It is super important for researchers and doctors to make reliable classifications using these details. In Figure 2, the diverse range of cardiomyopathies based on a deep analysis of tons of patient data can be seen.

CM covers a wide variety of heart diseases with different symptoms, causes and outcomes. Making accurate diagnoses for these heart conditions is crucial for the right treatment and predicting how things will turn out. There is other categories to think about like where genetic are located or what shows up on imaging tests, all mixed in with some electrical info. By looking at all these databases together, it is easier to spot the different types of cardiomyopathies and what sets them apart from each other. Combining all this data can help create a better way to categorize these conditions, which is key for improving how treat the patients and making personalized care plans for them.

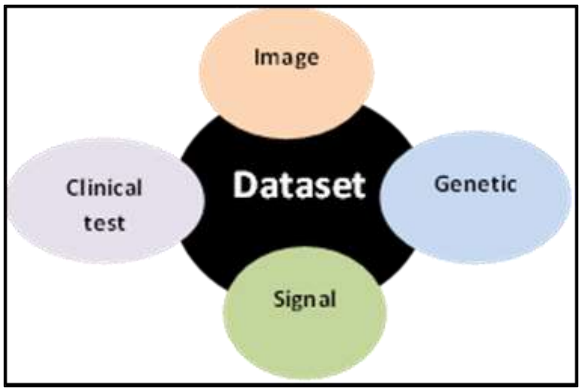

Fig. 2. CM dataset

3.1.1 Image based classification technique

Sangha *et al.,* [21] used deep learning to diagnose HCM. Their study demonstrated that ECG images obtained from 12 leads, without relying on raw voltage data, were highly sensitive in diagnosing HCM. Patients were included who were up to one-month prior study had HCM features by echocardiography or CMR (thicker interventricular septum). Then, external electrocardiogram images, UK Biobank cohort and YNHH were used to validate the model. For internal and external validation, the AUROC of the diagnostic accuracy across those different formats and calibrations was as high as 0.96 and 0.94 respectively. The model was based on a population-based case control study of approximately 67,000 individuals having ECGs at 124,553 instances.

Currently, Wu *et al.,* [22] are running a study on the ability of a deep learning model to detect and predict arrhythmias in cases of HCM from cardiac ultrasound blood flow images. This study includes patient demographic info (age, body mass index, pulse rate, blood pressure (diastolic and systolic) and gender). Cardiac ultrasound images are analysed by the deep learning model by several parameters such as circulation intensity change rate, left ventricular ejection fraction (LVEF), left atrial volume index (LAVI) , E/e' ratio, vertebral area change rate, mean EL value and mean blood flow velocity. By applying the model, the main risk factors for arrhythmia in individuals with hypertrophic CM were revealed: LAVI, E/e' ratio, rate of change of hemodynamic intensity, rate of change of intervertebral space, mean EL value and mean blood flow velocity, thus demonstrating the model's success.

3.1.2 ECG based classification technique

To develop an AI system that can diagnose HCM from 12 lead ECGs, Ko *et al.,* [23] conducted a study. To train and test their CNN model, the research used digital ECG data from 2448 patients with hypertrophic CM and 51153 control patients without HCM. The CNN was used on a different dataset of 12,788 normal people and 612 patients with HCM to assess its performance in deciding HCM. Both the model for training and validation samples yields AUC of 0.95. In this study, an optimal probability threshold for hypertrophic CM was 11% and the Confidence Interval (CI) for this study was between 0.94 and 0.97. This was done on the test dataset and when the threshold applied, the AUC from the Convolutional neural networks was 0.96 (95 % CI 0.95–0.96), specificity 90 % and sensitivity 87 %. The AUC for patients with left ventricular hypertrophy was 0.95 (95% CI: 0.94–0.97) and 0.95 (95% CI: 0.90–1.00) in patients with normal electrocardiogram. In younger patients, sensitivity of the model was 95% and specificity 92%. this model still requires further work for an external validation.

In this work, Silveri *et al.,* [24] aimed to classify dilated CM using a machine learning (ML) approach that utilizes heart rate variability (HRV). Unlike all previous studies that relied on HRV measurements to identify dilated CM, this study included 972 participants and used linear and non-linear HRV, left ventricular ejection fraction (LVEF), gender and age as clinical screening elements. The goal was to find potential diagnostically associated indicators as well as early-stage detection of DCM. The initial set of parameters was reduced using stepwise regression and principal component analyses where it was input into classification and regression trees (CART). The best performance of the classifier was achieved using with LFEF, sex and the LF/HF ratio as inputs and an accuracy of 97% and an AUC of 95%.

Siontis *et al.,* [25] identified HCM using a deep learning system trained on 12-lead ECGs. However, the study also revealed that the models' high performance was not solely due to the discrete data on which they were built. The researchers found that saliency maps could be used to identify electrocardiogram regions contributing to Convolutional neural networks accuracy in HCM patients. An updated CNN model was developed using median beats and a single lead (Lead I) while maintaining the same research strategy and sample size as the original 12-lead CNN model. This new model, which matched patients by age and sex, included 3047 HCM patients and 63,926 non-HCM controls. A separate set of 100 patients with a high artificial intelligence electrocardiogram-hypertrophic CM probability score was used to construct and visually evaluate saliency maps for the single-lead Convolutional neural networks model. The primary objective was to identify the electrocardiogram segments that contributed most to the model's ability to detect hypertrophic CM.

A pre-trained CNN [26] was developed to analyse 12-lead electrocardiogram waveforms from patients with known left ventricular hypertrophy (LVH), a condition associated with cardiac diseases such as cardiac amyloidosis, HCM, aortic stenosis and, hypertension, among others. A logistic regression model was then applied to assess the predictive capabilities of patient age, gender and 12-lead numerical electrocardiogram waveform data—referred to as "LVH-Net"—in relation to LVH aetiologies.

To further validate the robustness of LVH detection systems in single-lead data (such as mobile ECGs) and assess their performance when simplified to a single diagnostic lead, two deep learning models were developed: one trained using only lead I ("left ventricular hypertrophy -Net Lead I") and the other using only lead II ("left ventricular hypertrophy -Net Lead II").

The LVH-Net model demonstrated varying receiver operating characteristic (ROC) curve areas based on specific LVH causes:

i. Cardiac amyloidosis: AUC = 0.95 (95% CI, 0.93–0.97)
ii. HCM: AUC = 0.92 (95% CI, 0.90–0.94)
iii. Aortic stenosis-related LVH: AUC = 0.90 (95% CI, 0.88–0.92)
iv. Hypertensive left ventricular hypertrophy: AUC = 0.76 (95% CI, 0.76–0.77)
v. Other left ventricular hypertrophy cases: AUC = 0.69 (95% CI, 0.68–0.71)

Even the single-lead models demonstrated the ability to differentiate between various LVH causes. Specifically, in diagnosing HCM, the one-lead, median-beat Convolutional neural networks achieved performance comparable to the full 12-lead electrocardiogram model, with an Area Under the Curve of 0.90 (95% CI, 0.89–0.92).

Among 100 individuals in a separate HCM cohort, saliency maps identified the ST-T segment in 92 electrocardiograms, the atrial depolarization segment in 12 and the QRS complex in 5. These results indicate that the models effectively distinguish different sources of LVH.

3.1.3 Genetic based classification technique

Alimadadi *et al.,* [27] explored the use of ML to classify clinical cardiomyopathies based on cardiac transcriptome data, potentially revolutionizing diagnostic approaches. Five ML algorithms—svmRadial, elastic net (ENet), random forest (RF), pcaNNet and decision tree (DT)—were trained using RNA-Seq data from left ventricular tissues of 59 non-failing (NF) participants, 41 patients with DCM and 47 patients with ICM.

The initial ML classification results showed that NF vs. DCM achieved an accuracy of approximately 93% (svmRadial), NF vs. ICM around 82% (RF) and dilated CM vs. ischemic CM around 80% (ENet and svmRadial). Afterward, ML models were retrained using highly correlated genes (HCGs): with 50 highly correlated genes for non-failing vs. dilated CM, 68 highly correlated genes for non-failing vs. ischemic CM and 59 highly correlated genes for dilated CM vs. ischemic CM. RF achieved over 90% accuracy for non-failing vs dilated CM, pcaNNet was at about 90% for NF vs. ischemic CM and roughly 85% for dilated CM vs. ischemic CM on the retrained models. In addition, this study showed that the identified HCGs participate in cardiac dysfunction, including cardiomyopathies, hypertrophy and fibrosis.

Smole *et al.,* [28] advanced a new ML-based risk stratification tool to predict the risk of developing HCM over a five-year period and compared it with traditional statistical models, its predictive accuracy was evaluated. The study examined data from 2,302 patients, taking into genetic, clinical study, medication, condition-related factors and account demographic. The SHAP (SHapley Additive Interpretations) way providing interpretability for the four classification models used.

Adverse cardiac events considered were heart failure (HF), sudden cardiac death (SCD), implantable cardioverter defibrillator (ICD) activation, ventricular tachycardia (VT) and mortality. Compared to conventional risk stratification models for sudden cardiac death, CVD mortality and all-cause mortality, the ML method provided better results with AUC improvements of 17%, 9% and 1% respectively. The best performance was shown by the boosted tree classifier for overall risk prediction (Area Under the Curve of 0.82) and for VT (Area Under the Curve = 0.90), HF (Area Under the Curve = 0.88) and implantable cardioverter defibrillator activation (Area Under the Curve = 0.87).

3.2 Overview of Current Systems

In precision medicine (PM), modern technology and Internet and communication technology (ML/AI) is now just beginning to be considered as being pertinent to diagnosis and risk stratification.

However, there are existing screening models for hypertrophic CM, including predictive models based on statistical approaches.

ML and AI are among the recently recognized modern technologies that have value for diagnosis and risk stratification, in the modern world of precision medicine. Traditional screening models for HCM base on statistical prediction methods, whereas recent studies show the existence of machine learning based approaches. Chen *et al.,* [29] developed a machine learning model for prediction of one-year cardiovascular events in patients with severe DCM. Information Gain (IG) was used to analyse 32 clinical characteristics available for 98 patients from 2 centres and pivotal predicting dimensions as left atrial size (Information Gain = 0.240), QRS duration (Information Gain = 0.200) and systolic blood pressure (Information Gain = 0.151), were identified using data from 98 patients between 2 centres. The model was trained on the Naïve Bayes classifier and the AUC of the model was evaluated by 10- fold cross validation in the severe DCM individuals, for which an Area Under the Curve of 0.887 (95% CI, 0.813–0.961) was achieved.

Also, CNNs were applied in the work of Germain *et al.,* [30] for the classification of cine-MR images of CM. In the study, 1,200 sequences were analysed and 395 were classified as normal, 394 as DCM and 411 as HCM. utilizing the VGG models, we achieved accuracy of 0.982 ± 0.009 cross validated which met the implementation of experienced cardiologists and radiologists. Processed images amended accuracy by 5%. In another study, Nasimova *et al.,* [31] developed a convolutional neural network -based model for classifying echocardiography video data, achieving an accuracy of 98.2%. Their earlier work introduced an automated approach using ECG data for CM and myocardial infarction detection, with a CNN-based model correctly diagnosing CM 91.1% of the time despite similar ECG patterns between conditions [32].

Adedinsewo *et al.,* [33] from the Mayo Clinic designed a deep learning model to identify CM in pregnant and postpartum women using ECG data. Among 1,807 participants, the model achieved an Area Under the Curve of 0.89 for LVEF <35% and 0.87 for LVEF between 45% and 50%. Black and Hispanic women had a higher AUC (0.95) than White women (0.91). Compared to a traditional multivariable model incorporating demographic and clinical data (AUC = 0.72) and natriuretic peptides (AUC = 0.85–0.86), the deep learning approach demonstrated superior predictive power.

Further research highlights deep learning's potential in HCM diagnosis, with CNN-based models achieving up to 98.53% accuracy through data augmentation techniques like colour filtering and rotation. Optimizers such as Sharifrazi *et al.,* [34] and AlShemmary *et al.,* [35] were explored, demonstrating improvements over traditional augmentation methods. These findings suggest that integrating AI and ML can enhance diagnostic accuracy, but continued advancements are needed to refine models for broader clinical applications.

3.3 Analytical and Comparative Analysis

This section reviews various CM detection models, focusing on the strengths and accuracy of recent studies. Feature extraction algorithms have significantly improved classification systems, achieving high accuracy across datasets. While some studies focus on machine learning techniques, others explore new deep learning models, especially those using neural networks [36].

To enhance classification efficiency, several studies have improved feature extraction approaches (Table 1). Many researchers rely on CNNs as their primary deep learning model. Table 1 summarizes the performance results, allowing for a clear comparison of models.

Performance metrics reveal varying success rates based on the CM type and dataset. For example, CNNs achieved AUCs as high as 0.96 in HCM detection using ECG data, while machine learning models like random forests and SVMs showed an AUC of 0.82 for HCM using clinical and genetic data.

Traditional methods like CART for DCM reported a slightly lower AUC of 0.95. These comparisons highlight the superiority of CNNs in diagnostic accuracy but emphasize the need for diverse data and robust validation across different patient populations.

Despite these advances, most studies focus on diagnosing a single type of CM, primarily HCM, with different datasets used for different diseases. There is a need for an integrated system capable of diagnosing multiple types of cardiomyopathies by combining image, signal and genetic data.

Five years ago, the shift to genetic datasets occurred due to the limited availability of diagnostic medical devices in many regions, especially in developing countries. This has resulted in a lack of imaging data for CM research. A comparison of accuracy rates among image, signal and genetic datasets has shown varying levels of performance, highlighting the importance of dataset choice in diagnosis.

4. Methodology Enhancements

The study's framework details data pre-processing, feature selection, model architectures, validation and hyper parameter tuning, while also emphasizing transfer learning and dataset impact on classification performance.

i. Data Preprocessing: A structured preprocessing pipeline was implemented to ensure high-quality input data for CM classification. Key steps include:

- Data Cleaning: Removal of incomplete or corrupted records.
- Normalization & Standardization: ECG signals and CMR images were normalized using Min-Max Scaling or Z-score normalization.
- Data Augmentation: Techniques such as random rotations, flipping, contrast adjustments, noise injection (for imaging data), time-warping and signal masking (for ECG signals) were applied to mitigate data imbalance and improve generalization.

ii. Feature Selection: To optimize model performance and computational efficiency, the study employed:

- Statistical Methods: ANOVA F-tests and Chi-square tests for feature importance assessment.
- Dimensionality Reduction: Principal Component Analysis (PCA) to retain informative components while reducing redundancy.
- Domain-Specific Features: Extraction of clinically relevant ECG parameters, including R-R interval variability and QRS complex characteristics, to enhance classification accuracy.

iii. Model Architecture and Training: Multiple deep learning architectures were evaluated, including EfficientNetV2S, ResNet and CNN-based models. The architectures incorporate:

- Convolutional layers for hierarchical feature extraction.
- Batch normalization & dropout layers (0.3–0.5) to enhance stability and prevent overfitting.

ReLU activation in hidden layers and Softmax/Sigmoid in output layers. For ECG-based classification, pre-trained EfficientNetV2S and ResNet models were fine-tuned using transfer learning, leveraging prior knowledge for improved adaptation to the dataset.

Table 1
An overview of the articles that considered for the project on arrhythmia classification using AI

Ref.	Database	CM Type	Classification Methods	Classification Results	Limitations
Machine learning algorithms					
[28]	Personal information, medical history, genetic information, pharmaceuticals and occurrences connected to illness	HCM	Random forest (RF), SVM, Boosted trees and Neural-Networks	AUC of 0.82	- Developing standards for the many data transformations used in cardiology-related machine learning applications would be beneficial. - Running a sensitivity analysis on the data to see how different timeframes for the patient's records and risk assessments affects the accuracy levels reached. - The research presupposed that the model would not change over time and that all data was accessible prior to applying machine learning. To find out whether risk variables alter over time, we may test how well incremental updates work with the new patients' data.
[24]	ECG Holter monitor	DCM	CART	Accuracy of 97%, AUC of 95%	The scope of the work was restricted to recognizing a single category through the utilization of a single machine learning technique.
[27]	RNA Seq data	DCM, ICM and nonfailure controls (NF)	A variety of neural networks, including svmRadial, pcaNNet, DT, ENet and RF, in addition to support vector machines and elastic nets.	The results show that NF vs. DCM achieves 90% accuracy (RF), NF vs. ICM achieves around 90% accuracy (pcaNNet) and DCM vs. ICM achieves about 85% accuracy (pcaNNet and RF).	Each two types were classified separately
[29]	Thirty-two clinical features	DCM	Naive Bayes classifier	AUC of 0.887	The author's use of only one ML method on a small dataset resulted in lower generalization performance.

Deep learning algorithms					-
[21]	Images generated from ECG	HCM	CNN based on EfficientNet-B3 architecture	AUROC of 0.96	- Using the same samples for training and testing can introduce bias into the model and reduce its generalizability, since the 126,203 12-lead ECGs were collected from 68,109 individuals. - It takes more time and a complicated method to generate a picture from an electrocardiogram (ECG).
[23]	ECG	HCM	CNN	AUC of 0.96	This single-centre study's applicability to other settings is uncertain due to a high proportion of referral patients. Despite validated HCM diagnoses, some patients with athletic heart conditioning or non-HCM LVH may have been misclassified. Data on race, geographic origin and athlete status were unavailable. The AI model performed best in younger adults, suggesting potential for adolescent HCM screening, though no subjects under 18 were included. Additionally, the lack of "explainability" in neural networks remains a limitation, though understanding the features contributing to model performance is under active investigation.
[25]	ECG	HCM	CNN	AUC of 0.90	Subjective interpretation restricted the determination of the ECG segment highlighted by the CNN model, though ambiguous cases were infrequent. The analysis focused only on patients with known HCM and a high 12-lead AI-ECG-HCM score, excluding those with false AI-ECG results. Saliency maps were based on a simplified model using only the median beat from limb lead I, which may not capture additional insights from other leads. Additionally, the exact timing of the HCM diagnosis was not available in the dataset.

[26]	ECG	Aortic stenosis, hypertension, cardiac amyloidosis, hypertrophic CM and other reasons	CNN	CM AUROC 0.95, hypertension LVH 0.76, aortic stenosis LVH 0.90 and other LVH 0.69.	- Individuals with numerous LVH aetiologies may be misclassified if LVH CM is defined using terms that are mutually exclusive. - Classification of hypertrophic CM and cardiac amyloidosis might be made easier by relying on diagnostic data that is considered to be of the highest quality. - Undiagnosed transthyretin amyloidosis may lead to misclassification. - The model cannot classify athletic heart, rare LVH causes or cardiac amyloid subtypes present in the dataset. - The predominantly older and white study population limits generalizability. - Consistent performance across sex strata needs further validation in larger samples. - Deriving and validating the model within two referral hospitals may introduce selection bias, necessitating demonstration of generalizability to other settings.
[30]	Cinema MR scans of heart conditions	HCM and DCM	CNN (VGG model)	Accuracy of 0.982 ± 0.009	Only cine-MR was analysed, which is insufficient for diagnosing overload diseases; it is in the early stages of using artificial intelligence in this field; and it considers only a subset of cardiomyopathies.
[33]	ECG data	Left ventricular ejection fraction (LVEF)	Pretrained CNN	Black women had a greater area under the curve (0.95) and Hispanic women had a higher one (0.98) with LVEF levels of 35% or lower than White women (0.91).	Potential patient misclassification due to diagnosis code-based sample selection, selection bias from requiring both ECG and echocardiogram, underrepresentation of minority women, inaccurate BMI assessment, small sample size for the multivariable model and natriuretic peptides analysis due to missing data without imputation and results that are hypothesis-generating.
[32]	ECG data	Myocardial infarction (MI) and CM	CNN	Accuracy of 91.1%	The CNN network architecture used is simplified, with a reduction in the number of filters as the layers increase. However, this can result in the loss of important patterns, particularly when larger filters are used.

[34]	Cardiac magnetic resonance (CMR) images	HCM	CNN	Accuracy of 98.53%	This work is not fully automated, requiring expert quality control. Data were collected from a single hospital, potentially affecting reliability. To enhance accuracy, data from various healthcare centres are needed. Additionally, the model has not been tested with poor-quality images from patients who cannot hold their breath or have implantable devices or atrial fibrillation.

iv. Model Validation and Hyper Parameter Tuning: To ensure robust performance evaluation, the following strategies were employed:

- Cross-Validation: A 5-fold stratified cross-validation approach assessed model consistency.
- Hyper parameter Optimization:

- Learning rate: Tuned from 0.001 to 0.0001 using Grid Search.
- Batch size: Evaluated at 16, 32 and 64.
- Optimizers: Adam and SGD with momentum (0.9) to balance convergence speed and stability.
- Epochs: Set between 50 and 100, guided by early stopping criteria.

v. Transfer Learning Utilization: Transfer learning played a crucial role in improving DL models, particularly given the limited availability of medical data. Pre-trained convolutional neural networks on large-scale datasets (e.g., ImageNet) provided a strong foundation for feature representation. Fine-tuning the final layers allowed adaptation to CM classification tasks, improving convergence speed and model stability. The effectiveness of transfer learning varies based on dataset similarity. However, performance impact depends on dataset characteristics and it is beneficial for medical imaging. This study analyses the effect of transfer learning on classification performance across different architectures and datasets to achieve an optimal balance between proficiency and generalizability.

A two-stage validation approach is employed in order to complete a comprehensive evaluation. A 5-fold stratified cross validation based internal validation strategy was carried out for reducing bias and validating the stability of the model across different dataset partitions using performance metrics such as accuracy, AUC-ROC, sensitivity and F1 score to assess Durability. The independent datasets that were used for external validations had different demographics, different data types and different acquisition protocols. Cardiac magnetic resonance (CMR) images, electrocardiogram (ECG) signals, etc., from these sources like M&M, PTB-XL and clinical datasets from different medical institutions were provided these datasets.

As it is known that using data from a single source comes with the possibility of risks, cross dataset validation was carried out by testing the model against the data sourced from different hospitals. According to this approach, adaptively to different data distributions is guaranteed while potential dataset-specific limitations can be discovered and appropriate model adjustments need to be done. Since the domain transformation represents an urgent problem in medical artificial intelligence because the patient's data varies, for example, due to age, sex or differences in ways to obtain data, we have created some counter -measures. To reduce the contradictions between data groups, features standardization and field adaptation have been applied and the sub -group performance analysis was made to assess the effectiveness of the model through various demographic groups. Model interpretability techniques such as Grad-CAM were also used to select features responsible for a model’s decisions and thus increase trust in its predictions.

The generalizability of model performance was further evaluated in different types of clinical environments for instance, different hospitals that do not have the same type of diagnostic tool or imaging technology. Results were cross compared with other existing state of the art models and insights obtained on the model’s adaptability and reliability for deployment in the real world were sought. Although external validation was conducted, further testing on large-scale, multi-centre datasets remains essential to strengthen confidence in the findings. Future research efforts will focus on expanding validation cohorts to include more diverse geographical and demographic populations, establishing collaborations with additional medical institutions to access broader datasets and exploring federated learning approaches to facilitate model training across multiple hospitals while

preserving patient data privacy. These efforts will enhance generalizability without compromising confidentiality.

5. Methodology for Selecting Studies and Comparing Classification Models

A comprehensive and systematic approach was employed to select relevant studies, extract pertinent data and compare various classification models used in the domain of CM diagnosis [37].

Traditional models of classification often use only one source of data, for instance a CMR imaging or an ECG signal. As single source data may not be able to separate between subtypes of CM. Integration of multiple data modalities provides several benefits including a better clinical accuracy, a better model generalization and a different feature representation. However, the structural information in the heart can be obtained from imaging data such as CMR and echocardiography, which can be used in the diagnosis of HCM and DCM. Real time cardiac electrical activity is captured in other physiological signals like ECG, which is important for detecting arrhythmias of CM. Early risk assessment is also provided by genetic data which help to identify genetic mutations associated with the cardiomyopathies to respond proactively to the disease based on hereditary mutations appearing before the appearance of clinical symptoms.

These data sources are integrated into multimodal learning models in order to obtain a better diagnosis. Classification precision may be improved with anatomical, physiological and genetic markers using the aids of AI driven approaches. Multiple data streams are also integrated which makes the models less vulnerable to the noise or bias of any one modality improving overall stability and reliability of the models. Recent advances in AI have brought in basis of multimodal deep learning framework to process heterogeneous dataset, hybrid attention mechanisms emphasizing on salient feature of modalities and transformer architectures for handling complex multimodal interaction. Innovation of these procedures leads to better predictive performance and integrated insight into CM.

The AI Model multimodal that includes ECG signals, CMR photography and genetic data, Figure 3 shows this integration. The features extracted from these sources are processed in a multi layered neural network (MNN) and finally a final CM classification diagnosis is produced. This theoretical framework highlights that the integration is not simply a technical improvement but rather, a scientifically minded methodology, that increases the reliability of the diagnostic and model generalizability in the different clinical environments. The current study highlights the advantages of this approach, but further research is needed to enable adaptive AI to consistently integrate heterogeneous data sources into real-time clinical applications.

By merging longitudinal studies including imaging, bio signals, genetics and molecular biomarkers in the classification scope of CM, method can be extended to capture more far-reaching insights of the disease mechanisms and increase its accuracy.

After Łajczak *et al.,* [38] recently showed that the use of AI-based models can achieve high diagnostic accuracy for myocarditis and can be used in cardiac diagnosis. Studying metabolomics and proteomics has also revealed novel biomarkers associated with heart failure and atrial fibrillation, which are related to disease progression and the use as well as inclusion in CM classification models [39]. futurity research should concentrate on developing progressive ML models that merge multimodal data sources to improve diagnostic accuracy, Based on these insights. Furthermore, multivariate analysis using AI can also help to identify unknown factors of risk ultimately improving early detection and development of personalized strategies for treatment of CM. Improving this aspect of field will broaden what is known about disease progression and optimize patient outcomes.

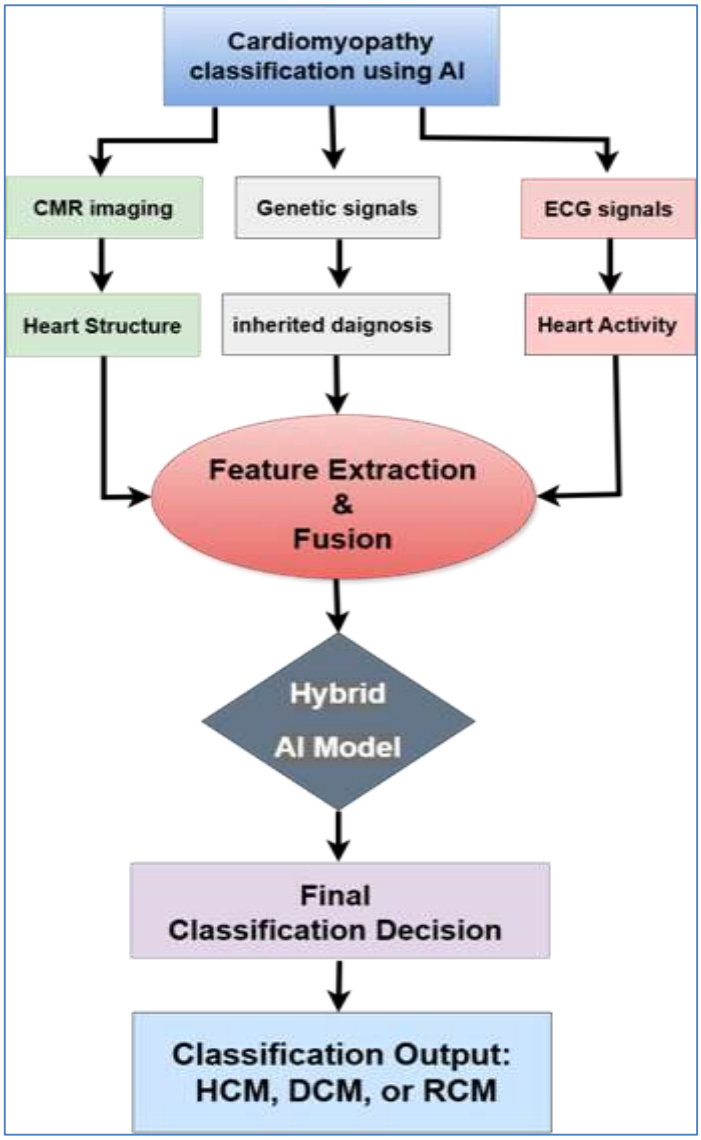

Fig. 3. Use of AI for the integration of multimodal data for CM classification

5.1 Selection of Studies

The literature search was conducted using multiple databases, including IEEE Xplore, PubMed, Google Scholar and Scopus. To make this search strategy broad yet targeted, the keywords for the search included 'CM', 'classification', 'DL', 'ML' , 'CNN', 'transformer', 'diagnosis' to have a selection of studies including relevant ones.

In this regard, studies were selected based on the following specific criteria:

i. Published in peer-reviewed journals or conferences
ii. Involving the use of machine learning or deep learning techniques for CM classification
iii. Providing quantitative results on model performance, such as specificity, accuracy, AUC and sensitivity. The studies were excluded without enough methodological detail or which did not statement performance metrics.

5.2 Data Extraction

From each selected study, data points that are key were extracted; kind of CM addressed, dataset size and source, feature selection methods, data pre-processing techniques, model architectures, assessment metrics and outcomes. In this kind of extraction, full information was ensured and comparative analysis could be tightly held because of it.

5.3 Comparison of Classification Models

The extracted data were standardised to allow for a fair comparison on common metrics such as specificity, AUC, accuracy and sensitivity. Based on the kind of CM the study addresses (i.e., hypertrophic, dilated) as well as the type of data used (i.e., MRI images, ECG signals) and the model type of the study (i.e., traditional machine learning models, CNNs, Swin Transformers), the comparative analysis framework grouped studies.

5.4 Performance Analysis

In the analysis, there were the strengths and weaknesses of all sorts of models in comparison to each other. For example, using a newer transformer architecture like Swin Transformer, a superior capacity to capture long range dependencies and deal with more complex spatial patterns in the images can be achieved (as compared to traditional CNNs) that are more depending on local features.

While CNNs were generally very accurate in some problems, they struggled with the spatial details and the semantic connexions over long distances. Other issues were addressed by different types of transformer-based models since those have strong global attention mechanisms.

To protect data privacy, eliminate bias and improve transparency in an AI driven CM diagnosis, there were measures taken. Anonymization and encryption ponied patient identity to ensure adherence of GDPR and HIPAA regulations. Bias was reduced and favourable diagnostic results were achieved through efforts to incorporate other demographic groups in the training data. Interpretable AI techniques, such as attention maps and feature importance analysis, provided transparency in decision-making, fostering trust in the technology. Additionally, advanced encryption (AES-256), stringent access controls, regular security audits and staff training reinforced data security. Ethical considerations were upheld through informed consent and ethical review board approval.

6. Other AI Applications in CM

There has been a discovery, within the recent past, of newer way in diagnosing as well as managing the condition through artificial intelligence. Aside the use of machine learning for image classification, other AI technologies are currently being employed in different fields of CM diagnosis and clinical practice.

Sophisticated image analysis approaches based on deep learning methods serve as the basis for detecting such patterns and abnormalities in medical imaging information. These models improve diagnostic performances since they can discover aspects unfamiliar to human interpretation and hence offer valuable information concerning the onset of CM.

Another apparent area of AI is known as the NLP that deals with clinical notes and patient records. NLP enables computerized identification of such markers and risk factors from unstructured text and support in the diagnosis and treatment of the conditions.

Artificial intelligence -driven decision support systems are playing an increasingly vital role in CM management. By integrating data from imaging, electronic health records (EHRs) and genetic profiles, these systems provide real-time, evidence-based recommendations, improving clinical decision-making and enhancing patient results through more precise and timely interventions. However, successful implementation requires addressing several key factors, including system compatibility, ethical concerns and practical challenges.

Adequate integration with EHRs into the EHR, as well as intuitive user interfaces, can help in adoption, while overcoming such barriers as computational demands, regulatory limits, data bias and costs limits is still of the essence. Transparency in AI decision-making, compliance with data protection regulations and preserving the physician's role in clinical practice are crucial ethical considerations. Additionally, targeted training programs can help healthcare providers effectively interpret AI-generated insights and merge them into diagnostic and remedy performance. The key considerations [40]:

i. Ensure AI models are compatible with healthcare systems and provide intuitive interfaces.
ii. Address technical, regulatory and financial challenges to enhance accessibility.
iii. Leverage AI-driven decision support for more accurate and timely interventions.
iv. Maintain transparency, mitigate data bias and comply with privacy regulations.
v. Implement training programs to equip clinicians with AI-assisted decision-making skills.

The continued evolution of AI in CM diagnosis and treatment highlights its potential to advance medical knowledge and enable a more personalized approach to patient care.

7. Conclusion and Future Perspectives

This paper outlines the latest developments in detecting CM through the application of AI. This is achieved by an analytic and comparative study, which discovers the best methods of use in sensitive medical operations in real time. Different kinds of datasets and AI techniques for the identification of CM are reviewed and the effects of those techniques on the classification model's performance are discussed. This is in view of the commonality of the Internet that has restricted the availability of clinical data set, thereby complicating the analysis to a large extent. Most current detecting systems are primarily centred on the detection of HCM while only few detected all types of cardiomyopathies having incorporated image data, ECG and genetics. Based on the analysis of the classification of CM using artificial intelligence, future research prospects are identified. Therefore, it is essential to create unified clinical databases containing jointly the disparate data types like imaging, ECG, genetic test results and many more. In addition, it is necessary to invent detection systems that enable the classification of various types of cardiomyopathies. This work points out on the need to incorporate more than one method when conducting medical research. However, there are still some classifications using the methods of single factor analysis, those using integrated methods are becoming the trends. The inclusion of multiple databases enables improved comprehension of cardiomyopathies and spurring of the development of latest diagnosis and therapeutic approaches. The classification technique best discussed shows the future efforts and new data dimension including immune and metabolomics, should be incorporated in driving the classification system. The idea is to constantly progress and integrate to create the best approach towards the study of cardiomyopathies with the hope of improving patient results of and goodness of lifetime.

To enhance the impact of the current research, future studies could explore several promising avenues. Integrating multimodal data, such as imaging, genomic and clinical information, could lead

to more comprehensive diagnostic models. Developing AI-powered real-time diagnostic tools and persona remedy plans could improve clinical decision-making and patient results. Besides, the use of AI before onset of CM related symptoms may aid in early diagnosis of the high-risk populace and timely treatment. Finally, yet importantly, progressive use of AI for not only differential diagnosis and disease progression, possibilities of complications and steer long-term management strategies would further enhance patient interest.

Acknowledgement
This research was not funded by any grant.

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